A Supporting Information for "Police Shootings Statistics and Public Support for Police Reforms"

Contents

A.1 Reporting Standards

A.1.1 Hypotheses

Our hypotheses are reported in the main text and expanded on in the Supporting Information (Section A.2) and were discussed in our pre-analysis plan prior to data collection, available at https://osf.io/j5pc9/.

A.1.2 Subjects and Context

Eligibility and exclusion criteria. Our sample was recruited from a panel by YouGov. We sample adult residents from 10 large US cities (Dallas, Houston, Jacksonville, Los Angeles, New York City, Philadelphia, Phoenix, San Antonio, San Diego, and San Jose). The selection criteria for the included cities was based on data availability for the counts of police shootings.

Procedures used to recruit and select participants YouGov recruits participants from an opt-in panel via email.

Recruitment Dates The survey was fielded from December 14, 2021 to January 7, 2022.

Setting The survey was fielded online to respondents from the 10 large US cities listed in the text and above.

Response Rate 2,575 respondents were surveyed by YouGov. YouGov did not provide further information about the response rate.

A.1.3 Allocation Method

We randomly assigned 75% of respondents to treatment (split randomly and evenly across the three treatment groups) and 25% to control. The randomization of subjects across the treatment groups is further described in Section A.3, and Table A1 in Section A.4 shows a similar number of respondents assigned to each treatment group. We examined balance using F-tests of whether covariates predict treatment. With p-values of 0.194, 0.332, 0.115, and 0.689 for the control, Shot treatment, Killed treatment, and Armed treatment groups, respectively, we fail to reject the null that the covariates do not predict treatment and thus find evidence in support of balance.

A.1.4 Treatment

The treatment arms provide varying information about police shootings. The text of each treatment arm is provided in Section A.3. The control group received no information about police shootings after being asked for their estimate of the number of police shootings.

A.1.5 Results

Outcome Measures and Covariates We use five outcome questions to assess respondents' support for police reforms, along a 5-point Likert scale from strongly oppose to strongly support. We include covariates of city level fixed effects, demographic information (race, sex, age) and socioeconomic indicators (income, education) and political factors (partisanship, registered voter, ideology). Outcomes were preregistered unless noted in the text.

Statistical Analysis Analysis was conducted in R, and replication code is available. Table A1 in Section A.4 presents results in the form of means of the outcome variables by treatment.

A.2 Additional Information about Theory and Hypotheses

Police Excess. People might connect information about policing to the underlying state of the world. They may believe there is a state of the world that corresponds to the level of police violence. Accordingly, *ceteris paribus*, respondents may believe there is a need for lethal force by police as the number of police shootings they learn of increases. We call this the *police excess* mechanism. Under the police excess mechanism, individual preferences for current proposals to limit police discretion in the use of force and reduce police involvement in non-violent situations will increase as they acquire information about the number of civilians police shot in their city.

However, this is a statement only about the relative level of support across individuals. The police excess mechanism also offers predictions about the effect of our experimental treatment. In particular, the same information about police shootings may move some respondents against policy reform proposals while moving others in favor of them. Specifically, if a respondent is given a piece of information about police behavior that is below her prior belief about police behavior, she will update her belief about police behavior downward, and vice-versa.

H2. Under the police excess *mechanism, respondents learning there were more shootings in their city than they predicted will change their opinion, relative to the control condition, in favor of limitations on police power and involvement in non-violent events. Respondents learning there were fewer shootings in their city than they predicted will change their opinion against those policy proposals.*

Police Danger. An alternative way individuals may process information from police shootings is to update based not on police excess but about the nature of danger associated with policing. We can conceive of the state of the world as a metric of the danger police face when policing a city. This mechanism is one by which information about police shootings is an indicator of how much discretion and force the police need to be effective law enforcers. We call this the *police danger* mechanism. Under the police danger mechanism, respondents' support for policies to limit police use of force and reduce police involvement in generally non-violent events (e.g., traffic stops and mental health checks) will decrease as the number of police shootings of civilians they learn about for their city increases. If so, we should observe precisely the opposite effects predicted by H1.

H3. Under the police danger *mechanism, respondents learning there were more shootings in their city than they predicted will change their opinion, relative to the control condition, against limitations on police power and involvement in non-violent events. Respondents learning there were fewer shootings in their city than they predicted will change their opinion in favor of those policy proposals.*

A.2.1 Subgroup Heterogeneity

Some recipients of information about the number of civilians police shot in their city may receive it as a signal about the danger of policing (second mechanism), while others receive it as a signal about the excesses of policing (first mechanism). Despite these two theoretically-grounded sources of effect heterogeneity, there may be subgroup patterns to how respondents process information about police behavior, primarily along racial and partisan cleavages.

Effect Heterogeneity by Race. The U.S. has a long tradition of differential policing, in which white Americans and Black Americans have distinctly different experiences with and perspectives about policing (Soss and Weaver 2017; Peffley and Hurwitz 2010). This influences how they process information about the police generally and police shootings of civilians, specifically (McGowen and Wylie 2020; Porter, Wood, and Cohen 2021; Jefferson, Neuner, and Pasek 2021; Pickett, Graham, and Cullen 2022; Hansen and Navarro 2021; Boudreau, MacKenzie, and Simmons 2019). Consequently, "the persistent racial divide observed in responses to officer-involved shootings appears rooted in markedly different beliefs and expectations Blacks and whites hold about the behavior of Back Americans and the fairness of the criminal justice system" Jefferson, Neuner, and Pasek 2021, 1167. Accordingly, we posit that Black Americans have reason to be skeptical of or to discount claims of danger as essential to policing and they should be more likely than whites to exhibit evidence of the police excess mechanism. Specifically, we expect Black residents of cities are more likely than white residents to show evidence of the police excess mechanism.

Effect Heterogeneity by Partisanship. Studies of "perceptual bias" conclude that "people perceive the world in a manner consistent with their political views. The result is a selective pattern of learning in which partisans have higher levels of knowledge for facts that confirm their world view and lower levels of knowledge for facts that challenge them" (Jerit and Barabas 2012, 672). Political partisans in the U.S. view policing, from its purposes to its practices, differently, whereby policing is now a highly polarized public function (Eckhouse 2019; Haider-Markel and Joslyn 2017; Hansen and Navarro 2021). Generally, because of their more conservative law-and-order views, Republicans tend to be more supportive of the police as an institution and less troubled by lethal use of force by the police (McLean and Nix 2021). In short, Republicans are more likely than Democrats to "back the blue." The degree of partisan polarization about the police is perhaps wide enough to produce a greater effect than race when it comes to attitudes towards the police.

Furthermore, partisan-derived perceptual bias, according to Jerit and Barabas 2012, 672, "is exaggerated on topics receiving high levels of media coverage." Police shootings of civilians, generally, are highly prominent in the media, inclusive of broadcast, print, and social media Ferguson 2021. While the media regardless of ideological leaning tend to "legitimate" police violence (Hirschfield and Simon 2010), right-leaning media and news coverage of police shootings of civilians is more "pro-cop" and "law-and-order" than left-leaning media and news coverage. That may matter because sources of media and consumption of information are polarized by partisanship, too.

The partisan conditions in the U.S. should compound the likelihood that partisanship influences perceptions of police shootings and proposed reforms of policing (Boudreau, MacKenzie, and Simmons 2019; Hansen and Navarro 2021). Therefore, we expect that the policy stances of Republicans towards the police are more likely to manifest the police danger mechanism, whereas Democratic respondents are more likely to show evidence of the police excess mechanism.

Expectations about Effect Heterogeneity. Given our assumptions about partisanship and race, we expect to find the greatest evidence of the police danger mechanism among white Republicans and the greatest evidence of the police excess mechanism among Black Democrats (Eckhouse 2019). With respect to Black Republicans and white Democrats, we believe the most likely determinant of which mechanism shapes respondents' behaviors is partisanship, not race. Partisanship should outweigh racial identity with respect to the relative ordering of Black Republicans and white Democrats, relative to Black Democrats and white Republicans. To be clear, we expect that (a) white Republicans will be most likely to respond to information about police shootings consistent with the police danger mechanism; (b) Black Democrats will be most likely to respond to information about police shootings consistent with the police excess mechanism; (c) white Democrats will be more similar to Black Democrats than white Republicans in how they respond to information about police shootings; and (d) Black Republicans will be more similar to white Republicans than Black Democrats in how they respond to information about police shootings.

A.2.2 Treatment Heterogeneity

Finally, different pieces of information about police behavior may create different response patterns. We expect that the content of the information provided about police shootings of civilians will influence respondents' reactions. Additional information about the individuals police shot (armed or unarmed) or the outcomes of the shootings (fatal or non-fatal for the victims) will condition responses. In particular, given widespread media attention to unarmed victims of police violence and popular understandings of unarmed victims as "innocents," as well as research on how identities, characteristics, and perceived threats posed by victims and decedents of police shootings may influence public reactions to such incidents (Hine et al. 2018; McGowen and Wylie 2020; Burch 2021), we expect a positive association between the unarmed shooting rate and respondents' support for police reform.

We have mixed expectations regarding the receipt of information regarding fatal shootings. On one hand, a higher rate of fatal shootings may lead respondents — especially those who think that any killings are bad and/or that police have greater discretion and ability to disable potential threats non-lethally — to respond to this indication of police violence with increased support for reform. On the other hand, following the logic of Clark et al., Forthcoming, a lower rate of fatal shootings may indicate a lower threshold for police willingness to use force, leading respondents to support reforms aimed at limiting police power. Given these mixed expectations, we have no a priori prediction for the influence of the fatal shooting rate on respondents' support for police reform.

A.3 Additional Information about Methods

A.3.1 Collection of Police Records

We collected data on police shootings in 2020 for the largest U.S. cities, those with populations greater than 100,000. We submitted public records requests to police departments in each city. We received official reports (e.g., incident reports, firearms discharge reports, or spreadsheets) from a set of police departments in fulfillment of our public records requests or they directed us to data available from their websites. Ten cities provided data adequate for us to determine their reported total number of shootings of civilians, number of fatal shootings of civilians, number of non-fatal shootings of civilians, number of shootings of unarmed civilians, number of shootings of armed civilians, and the race of each civilian police shot.[9] The cities include Dallas, Houston, Jacksonville, Los Angeles, New York City, Philadelphia, Phoenix, San Antonio, San Diego, and San Jose. We assume the data on police shootings of civilians we received from the 10 cities were accurate.[10]

A.3.2 Sample and Ethics

The study population consists of U.S. adult residents across the 10 cities for which we obtained adequate data about police shootings of civilians in 2020. We fielded the survey experiment online through YouGov in December 2021 to a sample of 2,575 participants. Participants were recruited by YouGov via email from its pre-existing opt-in survey panel.

All YouGov panelists have given YouGov permission to contact them about participating in surveys YouGov conducts. For our particular survey fielded by YouGov, we included an IRB-approved script for informed consent as the first page of the survey. After reviewing this information, recruited individuals could decide whether or not to participate in the study, and individuals consented by clicking to agree to take part in the research study. The survey did not involve any deception and did not record any personally-identifying information.

9. Collecting such data, generally, is a challenge. This is because, as Matusiak, Cavanaugh, and Stephenson 2022, 487 and others (Williams, Bowman, and Jung 2019) explain, "the state of publicly available OIS [officer-involved shootings] information is limited with a small proportion of law enforcement organizations providing any data related to OIS incidents. Importantly, data presented by law enforcement agencies lack continuity as well. There is great variation in the type, classification, and quality of data presented that limits utility for the purposes of research as well as policy creation and evaluation."

10. Unfortunately, there is no independent means (e.g., national clearinghouse) for scholars to verify the accuracy of police data on shootings of civilians they receive. Scholars studying police shootings, after excluding shootings of canines and unintentional shootings of civilians, must assume accuracy, even as under-reporting of incidents of such shooting may be prevalent and systematic (Cook and Fortunato 2022). It is an inherent weakness for scholars using any types of police data and political sovereigns and citizens seeking to use police data to foster greater accountability from policing agencies.

A.3.3 Randomization, and Treatment Assignment

We randomly assigned respondents to a treatment group or a control group: three-fourths (75%) of respondents were treated by randomly exposing them to the number of police shootings of civilians in their city in 2020, and one-fourth (25%) of respondents did not receive this information and comprised the control group. The information on police shootings provided to treated respondents was factual; we did not alter the numbers we obtained from the reports provided to us by the 10 police departments.

Before receiving factual information about police shootings in their cities, all respondents (in both control and treatment) were asked to estimate the number of civilians that police officers of their local police agency shot in 2020. Respondents were prompted to provide their best guess. Subsequently, they were randomly assigned to one of four groups:

1. Treatment Group 1 (25% of respondents): Information – "According to [POLICING AGENCY NAME], its officers shot [NUMBER SHOT] people in 2020."
2. Treatment Group 2 (25% of respondents): Information – "According to [POLICING AGENCY NAME], its officers shot [NUMBER SHOT] people in 2020. [NUMBER KILLED] ([PERCENT KILLED]%) were killed. [NUMBER NOT KILLED] ([PERCENT NOT KILLED]%) were not killed."
3. Treatment Group 3 (25% of respondents): Information – "According to [POLICING AGENCY NAME], its officers shot [NUMBER SHOT] people in 2020. [NUMBER ARMED] ([PERCENT ARMED]%) were armed. [NUMBER UNARMED] ([PERCENT UNARMED]%) were unarmed."
4. Control Group (25% of respondents): No additional information

A.3.4 Outcome Measures

We use five outcome questions to assess respondents' support for police reforms, along a 5-point Likert scale from strongly oppose to strongly support. The police reforms discussed in the outcome questions are based on actual reform efforts in cities across the U.S. and on topics of popular conversation around policing reform. The outcome questions are as follows:

1. Some cities are proposing limiting armed police officer involvement in low-level traffic stops (e.g., for broken tail lights), relying instead on unarmed transportation workers for low-level traffic stops instead of police officers. Do you support or oppose this proposal?
2. A few cities are using more mental health workers or emergency medical technicians (EMTs) as "first responders" instead of police to deal with mental health emergencies. Do you support or oppose this policy?

3. A few cities are considering reducing their use of no-knock warrants, which allow police to immediately and forcibly enter a home without first announcing themselves. Do you support or oppose this policy?

4. Do you support or oppose reducing the legal protections that individual police officers have against being sued for their actions taken while on duty, commonly known as qualified immunity?

5. Do you support or oppose giving civilian oversight boards the power to investigate and discipline (e.g., suspend or fire) police officers for inappropriate use of force or other misconduct?

These outcome questions are similar to other recent survey questions in national polls. We consulted Roper iPoll and took inspiration from questions asked in surveys fielded by YouGov, Data for Progress, CATO, and Pew in 2020 and 2021. For example, in June 2020, Pew asked survey respondents to indicate whether they would favor or oppose giving "civilian oversight boards the power to investigate and discipline police officers accused of inappropriate use of force or other misconduct." Our survey similarly asked, "Do you support or oppose giving civilian oversight boards the power to investigate and discipline (e.g., suspend or fire) police officers for inappropriate use of force or other misconduct?" In addition, the reform efforts mentioned in our outcome questions are not specific to the cities in our sample. For theoretical reasons, as well as reasons related to statistical power, we opted to conduct one survey experiment across multiple cities with hypothetical reform proposals rather than separate studies within cities tailored to their unique policy environments. Moreover, while there are many other possible policing reforms that we could have asked about, we limited the survey to only the five outcome questions that we deemed most salient to the national conversation at the time in order to reduce multiple testing and to reduce the burden on survey respondents.

We also thought that it was possible that the treatments would move policy opinions on some reforms more than others. However, we expected that this would most likely depend on which high profile use of force incidents were the most salient and accessible in respondents' minds at the time of the survey (e.g., Philando Castile - traffic stops, or Breonna Taylor - no knock warrants). Without strong enough expectations to more specifically inform the design of our survey experiment, we turned to a pilot study. Based on the pilot study, we found stronger effects for the traffic stops outcome, and we therefore specified in our pre-analysis plan that we would devote specific attention to the traffic stops outcome in our analysis. As we state in our pre-analysis plan, there are some theoretical reasons to focus on this particular outcome as well: "traffic stops are the most common method through which individuals encounter the police and are thus the encounters for which respondents may be the most concerned about police violence." However, the results of our main YouGov survey experiment do not support this expectation.

A.3.5 MDE Calculations to Assess Power

We used simulations based on a pilot study to calculate minimum detectable effects (MDEs) along a range of possible sample sizes for our five main outcomes of interest. For these calculations, we used our anticipated sample size of about 2,200, the standard deviations of the outcomes as measured in the pilot, and the conventional 80% power and 5% significance levels. We also made comparisons between control and the pooled treatment group. Based on these calculations, we determined that our design had sufficient power to detect effects as small as 0.147 to 0.150 standard deviations (movement of about 0.19 to 0.22 points on the 5-point Likert scale) when comparing control to pooled treatment. These are relatively small effects according to the political psychology literature and in comparison to other survey experiments (Funder and Ozer 2019). While we did not find many sizable effects as a result of our treatments, our experiment was sufficiently powered to detect such effects.

A.3.6 Estimation of Average Treatment Effects

We use ordinary least squares (OLS) regression with covariate adjustment to estimate average treatment effects (ATEs). We use heteroskedasticity-robust standard errors and two-sided p-values to assess significance at the conventional 5% level, with corrections for multiple testing according to the Benjamini-Hochberg method. We included the following demographic covariates: race/ethnicity, partisanship, gender, age, education, household income, children, voter registration, and political ideology. We also include city fixed effects and three additional covariates that we measure in our survey: respondent estimates for the number of civilians shot by police in their city in 2020, respondent evaluations of police use of force in their city, and whether respondents have had police force used against them or someone they know.

A.3.7 Nonparametric Combination

We use the nonparametric combination (NPC) method (Caughey, Dafoe, and Seawright 2017) to conduct a single test of whether the combined evidence across our tests supports the theoretical expectation that statistics on police shootings affect citizens' support for police reform proposals. To implement the NPC method, we first calculate a vector of p-values for our main tests using our observed/actual data. Then, we randomly permute the treatment group labels in our data (with an experiment, all units are exchangeable) to create simulated data, and we run the same tests as for our observed/actual data to get p-values for each permutation. Next, we use the Fisher's product function (the recommended p-value combination function) to calculate a global test statistic for observed results and for each permutation. Finally, we obtain the combined significance level (global p-value) from the global test statistic. The global p-value is the proportion of permuted global test statistics that are at least as large as the observed global test statistic. A benefit of this method is that we are able to tailor it to the exact tests that we ran for our analysis.

Based on 10,000 permutations, we obtain a global p-value of 0.94, indicating that 94% of permutations in which treatment and control unit labels were exchanged resulted in combined test statistics at least as large as what we observed. It is therefore exceedingly likely that our informational treatments had no effect on respondents' expressions of policy preferences. As an additional test, we used the NPC method on only our results for the civilian oversight outcome, the outcome for which we found the most statistically significant and substantially large results. With a global p-value of 0.31, we still fail to reject the null that information on police shootings does not affect support for civilian oversight boards.

A.4 Results of Testing Pre-Registered Hypotheses

A.4.1 Means of Outcome Variables by Treatment

Table A1: Means of Outcome Variables by Treatment

Treatment	n	Traffic Stops	Mental Health	No Knock	Qualified Immunity	Civilian Oversight
Control	624	3.026 (0.052)	3.720 (0.053)	3.311 (0.059)	3.272 (0.053)	3.577 (0.050)
Shot	650	2.997 (0.051)	3.735 (0.049)	3.348 (0.056)	3.351 (0.052)	3.686 (0.047)
Killed	646	3.105 (0.050)	3.749 (0.049)	3.257 (0.058)	3.316 (0.053)	3.681 (0.049)
Armed	655	3.061 (0.050)	3.730 (0.048)	3.336 (0.055)	3.308 (0.052)	3.745 (0.046)

Each outcome variable was measured using a 5-point Likert scale from strongly oppose to strongly support. Means are reported with standard errors in parentheses.

A.4.2 Hypothesis 1: Overall Impact of the Informational Treatments

F-test p-value for treatments with traffic stops outcome: 0.053

t-test p-value for armed treatment with traffic stops outcome: 0.700

Table A2: Hypothesis 1 Results

	Traffic Stops (1)	Mental Health (2)	No Knock (3)	Qual. Imm. (4)	Civ. Oversight (5)
Shot	−0.065	−0.014	0.035	0.056	0.091
	(0.068)	(0.066)	(0.082)	(0.073)	(0.065)
Killed	0.117*	0.046	−0.025	0.057	0.129**
	(0.067)	(0.065)	(0.084)	(0.073)	(0.065)
Armed	0.026	0.006	0.017	0.028	0.180***
	(0.066)	(0.064)	(0.082)	(0.073)	(0.063)
Houston	0.140	0.122	0.137	0.414***	0.290**
	(0.111)	(0.110)	(0.135)	(0.118)	(0.113)
Jacksonville	0.110	0.031	0.247	0.056	0.111
	(0.138)	(0.140)	(0.166)	(0.158)	(0.148)
Los Angeles	−0.113	−0.193*	−0.187	0.094	0.011
	(0.114)	(0.114)	(0.137)	(0.125)	(0.116)
New York City	−0.126	−0.173*	−0.164	−0.0002	0.164
	(0.102)	(0.100)	(0.122)	(0.110)	(0.105)
Philadelphia	0.001	0.027	−0.019	0.009	0.190
	(0.130)	(0.125)	(0.160)	(0.141)	(0.126)
Phoenix	−0.126	0.111	−0.046	0.040	0.185
	(0.123)	(0.121)	(0.151)	(0.134)	(0.126)
San Antonio	−0.085	0.131	−0.030	0.324**	0.344***
	(0.123)	(0.121)	(0.149)	(0.132)	(0.124)
San Diego	−0.038	0.071	−0.223	−0.014	0.142
	(0.143)	(0.139)	(0.179)	(0.157)	(0.143)
San Jose	−0.047	−0.029	−0.110	0.201	0.425***
	(0.180)	(0.167)	(0.207)	(0.194)	(0.158)
Black	0.039	0.115*	0.001	−0.053	0.131*
	(0.072)	(0.066)	(0.088)	(0.079)	(0.068)
Hispanic/Latino	−0.086	0.015	−0.269***	−0.241***	−0.0003
	(0.064)	(0.064)	(0.079)	(0.069)	(0.064)
Other Race	−0.026	0.017	0.081	0.022	0.052
	(0.076)	(0.073)	(0.093)	(0.083)	(0.070)
Partisanship	−0.088***	−0.130***	−0.062***	−0.066***	−0.081***
	(0.016)	(0.016)	(0.019)	(0.017)	(0.016)
Female	−0.039	0.128***	−0.096	−0.118**	−0.055
	(0.048)	(0.047)	(0.059)	(0.053)	(0.047)
Age	−0.006***	−0.001	0.0003	−0.009***	−0.002
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)
Education	0.059***	0.066***	0.085***	0.034*	0.019
	(0.018)	(0.017)	(0.022)	(0.019)	(0.017)
Income	0.001	−0.002	0.017*	0.007	0.0003
	(0.008)	(0.007)	(0.009)	(0.008)	(0.007)
Children	0.030	−0.044	−0.189***	−0.114*	−0.127**
	(0.060)	(0.059)	(0.073)	(0.064)	(0.059)
Registered Voter	−0.076	0.008	0.077	−0.010	0.094
	(0.079)	(0.081)	(0.096)	(0.083)	(0.079)
Pol. Ideology	−0.315***	−0.283***	−0.258***	−0.267***	−0.285***
	(0.029)	(0.030)	(0.036)	(0.033)	(0.031)
Shootings Estimate	−0.00005	−0.00005	−0.00004	−0.0001	−0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
PD Rating	−0.234***	−0.187***	−0.089***	−0.169***	−0.197***
	(0.021)	(0.020)	(0.025)	(0.022)	(0.020)
UoF Experience	0.038	0.033	0.198***	0.121*	0.105*
	(0.055)	(0.054)	(0.068)	(0.062)	(0.054)
Constant	5.046***	5.202***	4.098***	4.983***	4.939***
	(0.167)	(0.175)	(0.206)	(0.190)	(0.178)
N	2,238	2,238	2,238	2,238	2,238
R^2	0.274	0.271	0.126	0.180	0.239
F Statistic (df = 26; 2211)	32.170***	31.668***	12.251***	18.725***	26.715***

*p < .1; **p < .05; ***p < .01
Notes: With robust SEs

A.4.3 Hypotheses 2 and 3: Updating Based on Priors

F-test p-value for interaction terms with traffic stops outcome: 0.934

Table A3: Hypotheses 2 and 3 Results

	Traffic Stops	Mental Health	No Knock	Qual. Imm.	Civ. Oversight
	(1)	(2)	(3)	(4)	(5)
Shot	−0.077	−0.016	0.002	0.039	0.087
	(0.073)	(0.071)	(0.085)	(0.077)	(0.070)
Killed	0.107	0.029	−0.038	0.069	0.104
	(0.071)	(0.069)	(0.087)	(0.077)	(0.069)
Armed	0.029	−0.009	0.0002	0.023	0.189^{***}
	(0.070)	(0.069)	(0.085)	(0.077)	(0.067)
Estimate Diff	0.014	0.032	0.004	0.029	0.004
	(0.034)	(0.032)	(0.041)	(0.034)	(0.032)
Houston	0.160	0.165	0.167	0.442^{***}	0.303^{***}
	(0.113)	(0.112)	(0.138)	(0.120)	(0.115)
Jacksonville	0.134	0.083	0.282^{*}	0.089	0.126
	(0.139)	(0.142)	(0.168)	(0.159)	(0.150)
Los Angeles	−0.105	−0.169	−0.168	0.110	0.009
	(0.115)	(0.116)	(0.139)	(0.126)	(0.118)
New York City	−0.129	-0.169^{*}	−0.166	−0.002	0.161
	(0.102)	(0.099)	(0.121)	(0.110)	(0.105)
Philadelphia	0.012	0.052	−0.006	0.019	0.200
	(0.131)	(0.125)	(0.160)	(0.141)	(0.127)
Phoenix	−0.103	0.158	−0.013	0.070	0.200
	(0.124)	(0.123)	(0.153)	(0.137)	(0.128)
San Antonio	−0.062	0.181	0.0005	0.350^{***}	0.362^{***}
	(0.125)	(0.123)	(0.151)	(0.134)	(0.126)
San Diego	−0.021	0.104	−0.200	0.004	0.155
	(0.144)	(0.140)	(0.181)	(0.158)	(0.144)
San Jose	−0.035	−0.007	−0.093	0.217	0.433^{***}
	(0.180)	(0.167)	(0.208)	(0.194)	(0.159)
Black	0.035	0.107	−0.005	−0.059	0.127^{*}
	(0.072)	(0.066)	(0.088)	(0.079)	(0.068)
Hispanic/Latino	−0.091	0.010	-0.275^{***}	-0.245^{***}	−0.005
	(0.064)	(0.064)	(0.079)	(0.069)	(0.063)
Other Race	−0.030	0.011	0.075	0.017	0.048
	(0.076)	(0.073)	(0.093)	(0.083)	(0.070)
Partisanship	-0.088^{***}	-0.129^{***}	-0.061^{***}	-0.065^{***}	-0.081^{***}
	(0.016)	(0.016)	(0.019)	(0.017)	(0.016)
Female	−0.037	0.128^{***}	−0.095	-0.120^{**}	−0.052
	(0.049)	(0.047)	(0.059)	(0.053)	(0.047)
Age	-0.006^{***}	−0.001	0.001	-0.009^{***}	−0.002
	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)
Education	0.058^{***}	0.066^{***}	0.084^{***}	0.033^{*}	0.019
	(0.018)	(0.017)	(0.022)	(0.019)	(0.017)
Income	0.0002	−0.002	0.017^{*}	0.007	−0.00005
	(0.008)	(0.007)	(0.009)	(0.008)	(0.007)
Children	0.033	−0.039	-0.183^{**}	-0.106^{*}	-0.128^{**}
	(0.060)	(0.059)	(0.073)	(0.064)	(0.060)
Registered Voter	−0.073	0.013	0.076	−0.016	0.104
	(0.079)	(0.082)	(0.096)	(0.084)	(0.079)
Pol. Ideology	-0.315^{***}	-0.283^{***}	-0.258^{***}	-0.266^{***}	-0.285^{***}
	(0.029)	(0.030)	(0.036)	(0.033)	(0.031)
PD Rating	-0.229^{***}	-0.177^{***}	-0.081^{***}	-0.162^{***}	-0.193^{***}
	(0.021)	(0.020)	(0.025)	(0.023)	(0.021)
UoF Experience	0.034	0.027	0.195^{***}	0.116^{*}	0.101^{*}
	(0.055)	(0.054)	(0.068)	(0.062)	(0.054)
Shot x Estimate Diff	0.013	−0.009	0.049	0.016	0.002
	(0.043)	(0.041)	(0.053)	(0.046)	(0.042)
Killed x Estimate Diff	0.021	0.030	0.026	−0.027	0.050
	(0.048)	(0.047)	(0.059)	(0.049)	(0.046)
Armed x Estimate Diff	−0.006	0.025	0.032	0.006	−0.014
	(0.046)	(0.045)	(0.057)	(0.049)	(0.045)
Constant	5.000^{***}	5.108^{***}	4.048^{***}	4.923^{***}	4.904^{***}
	(0.172)	(0.180)	(0.212)	(0.196)	(0.184)
N	2,238	2,238	2,238	2,238	2,238
R^2	0.275	0.274	0.127	0.181	0.240
F Statistic (df = 29; 2208)	28.856^{***}	28.679^{***}	11.077^{***}	16.867^{***}	24.001^{***}

$^{*}p < .1$; $^{**}p < .05$; $^{***}p < .01$
Notes: With robust SEs

For attentive respondents:

Table A4: Hypotheses 2 and 3 Results: Attentive Respondents

	Traffic Stops	Mental Health	No Knock	Qual. Imm.	Civ. Oversight
	(1)	(2)	(3)	(4)	(5)
Shot	−0.052	−0.045	−0.026	0.028	0.126
	(0.096)	(0.092)	(0.115)	(0.106)	(0.091)
Killed	0.056	−0.012	0.093	0.031	−0.004
	(0.095)	(0.090)	(0.116)	(0.106)	(0.093)
Armed	0.030	0.018	−0.014	0.029	0.253***
	(0.092)	(0.086)	(0.116)	(0.107)	(0.086)
Estimate Diff	0.007	0.042	−0.001	0.001	0.019
	(0.052)	(0.047)	(0.062)	(0.052)	(0.049)
Houston	0.109	0.246*	0.053	0.364**	0.221
	(0.149)	(0.136)	(0.177)	(0.157)	(0.144)
Jacksonville	0.151	0.197	0.182	−0.169	0.079
	(0.177)	(0.172)	(0.219)	(0.211)	(0.199)
Los Angeles	−0.169	−0.139	−0.163	−0.044	−0.012
	(0.150)	(0.141)	(0.174)	(0.161)	(0.140)
New York City	−0.248*	−0.236*	−0.265*	−0.149	0.040
	(0.134)	(0.122)	(0.150)	(0.140)	(0.129)
Philadelphia	0.003	0.067	−0.161	−0.068	0.034
	(0.163)	(0.148)	(0.198)	(0.182)	(0.158)
Phoenix	−0.201	0.305*	0.040	−0.038	0.126
	(0.170)	(0.156)	(0.206)	(0.183)	(0.168)
San Antonio	−0.213	0.173	−0.022	0.155	0.354**
	(0.164)	(0.150)	(0.187)	(0.172)	(0.156)
San Diego	−0.122	0.050	−0.407*	−0.295	−0.111
	(0.185)	(0.173)	(0.221)	(0.211)	(0.185)
San Jose	−0.133	−0.024	−0.280	0.089	0.357*
	(0.210)	(0.194)	(0.237)	(0.223)	(0.188)
Black	0.059	0.139	0.102	−0.094	0.220**
	(0.100)	(0.087)	(0.121)	(0.116)	(0.090)
Hispanic/Latino	−0.015	0.055	−0.349***	−0.167*	−0.047
	(0.083)	(0.079)	(0.102)	(0.089)	(0.077)
Other Race	−0.059	0.040	−0.080	0.101	0.061
	(0.097)	(0.089)	(0.120)	(0.104)	(0.088)
Partisanship	−0.088***	−0.119***	−0.047*	−0.062**	−0.084***
	(0.022)	(0.021)	(0.027)	(0.024)	(0.022)
Female	−0.083	0.120**	−0.109	−0.121*	−0.087
	(0.062)	(0.059)	(0.076)	(0.070)	(0.058)
Age	−0.005***	0.002	−0.001	−0.009***	−0.002
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)
Education	0.082***	0.066***	0.075***	0.030	0.044*
	(0.024)	(0.023)	(0.029)	(0.026)	(0.023)
Income	0.003	0.005	0.030**	0.014	−0.003
	(0.010)	(0.010)	(0.012)	(0.011)	(0.009)
Children	0.052	0.004	−0.142	−0.137	−0.107
	(0.080)	(0.074)	(0.097)	(0.090)	(0.076)
Registered Voter	−0.330***	−0.128	0.048	0.048	−0.019
	(0.110)	(0.108)	(0.140)	(0.120)	(0.113)
Pol. Ideology	−0.343***	−0.289***	−0.264***	−0.266***	−0.256***
	(0.039)	(0.036)	(0.048)	(0.044)	(0.039)
PD Rating	−0.232***	−0.184***	−0.118***	−0.172***	−0.216***
	(0.028)	(0.027)	(0.035)	(0.032)	(0.026)
UoF Experience	0.046	0.069	0.223**	0.155*	0.158**
	(0.071)	(0.066)	(0.090)	(0.084)	(0.064)
Shot x Estimate Diff	0.028	−0.010	0.033	0.039	−0.069
	(0.064)	(0.061)	(0.076)	(0.068)	(0.060)
Killed x Estimate Diff	0.048	0.019	−0.029	0.012	0.044
	(0.070)	(0.066)	(0.084)	(0.073)	(0.068)
Armed x Estimate Diff	0.016	0.054	0.052	0.054	−0.050
	(0.067)	(0.061)	(0.082)	(0.070)	(0.064)
Constant	5.278***	5.087***	4.299***	5.015***	5.098***
	(0.228)	(0.219)	(0.282)	(0.255)	(0.235)
N	1,311	1,311	1,311	1,311	1,311
R^2	0.318	0.300	0.148	0.201	0.272
F Statistic (df = 29; 1281)	20.584***	18.902***	7.703***	11.117***	16.540***

*p < .1; **p < .05; ***p < .01
Notes: With robust SEs

A.4.4 Hypothesis 4: Subgroup Heterogeneity

Table A5: Hypothesis 4: Black Democrats

	Traffic Stops (1)	Mental Health (2)	No Knock (3)	Qual. Imm. (4)	Civ. Oversight (5)
Shot	−0.157	0.017	0.148	−0.130	0.247
	(0.207)	(0.184)	(0.261)	(0.231)	(0.207)
Killed	0.038	0.127	−0.120	−0.324	0.321
	(0.211)	(0.192)	(0.271)	(0.233)	(0.202)
Armed	0.136	0.089	0.073	0.094	0.486**
	(0.216)	(0.211)	(0.314)	(0.266)	(0.197)
Estimate Diff	0.048	−0.027	0.055	−0.030	−0.017
	(0.077)	(0.083)	(0.115)	(0.088)	(0.088)
Houston	0.411	0.101	−0.023	−0.019	0.410
	(0.317)	(0.255)	(0.407)	(0.344)	(0.322)
Jacksonville	0.712**	−0.305	0.554	−0.653	0.433
	(0.359)	(0.374)	(0.478)	(0.456)	(0.385)
Los Angeles	−0.106	−0.712**	−0.622	0.309	−0.023
	(0.376)	(0.332)	(0.461)	(0.374)	(0.368)
New York City	0.074	−0.064	0.145	−0.290	0.274
	(0.276)	(0.219)	(0.349)	(0.303)	(0.286)
Philadelphia	0.202	0.213	−0.116	−0.604*	0.397
	(0.308)	(0.240)	(0.405)	(0.339)	(0.304)
Phoenix	0.627	0.524*	0.686	0.175	0.935**
	(0.541)	(0.296)	(0.617)	(0.575)	(0.375)
San Antonio	0.348	0.110	0.221	0.001	0.472
	(0.430)	(0.309)	(0.644)	(0.493)	(0.426)
San Diego	−1.070*	−0.196	−0.966	−0.077	0.904***
	(0.569)	(0.621)	(0.762)	(0.722)	(0.336)
Female	0.183	0.341**	−0.079	−0.145	−0.105
	(0.168)	(0.136)	(0.191)	(0.177)	(0.141)
Age	−0.005	0.001	0.005	−0.013**	0.006
	(0.005)	(0.004)	(0.007)	(0.005)	(0.005)
Education	0.046	0.031	0.023	0.136**	−0.010
	(0.051)	(0.046)	(0.070)	(0.061)	(0.050)
Income	0.005	0.017	0.055*	−0.020	−0.013
	(0.024)	(0.018)	(0.030)	(0.026)	(0.022)
Children	−0.160	−0.044	−0.245	−0.580***	−0.035
	(0.191)	(0.151)	(0.215)	(0.194)	(0.173)
Registered Voter	0.623*	0.053	−0.213	0.240	0.552
	(0.318)	(0.318)	(0.349)	(0.368)	(0.343)
Pol. Ideology	−0.175*	−0.159**	−0.039	−0.123	−0.264***
	(0.093)	(0.081)	(0.104)	(0.091)	(0.082)
PD Rating	−0.154**	−0.016	0.071	0.006	−0.091*
	(0.066)	(0.050)	(0.078)	(0.068)	(0.055)
UoF Experience	0.174	0.196	0.187	0.144	0.158
	(0.166)	(0.140)	(0.200)	(0.178)	(0.146)
Shot x Estimate Diff	−0.003	−0.007	−0.036	−0.076	0.055
	(0.116)	(0.102)	(0.164)	(0.142)	(0.115)
Killed x Estimate Diff	−0.094	−0.078	0.086	−0.146	−0.008
	(0.131)	(0.152)	(0.183)	(0.133)	(0.144)
Armed x Estimate Diff	−0.030	0.015	0.061	0.061	−0.025
	(0.139)	(0.121)	(0.181)	(0.139)	(0.126)
Constant	3.251***	4.032***	2.885***	4.273***	3.581***
	(0.582)	(0.595)	(0.738)	(0.668)	(0.594)
N	310	310	310	310	310
R^2	0.138	0.117	0.075	0.129	0.149
F Statistic (df = 24; 285)	1.896***	1.580**	0.969	1.757**	2.076***

*p < .1; **p < .05; ***p < .01
Notes: With robust SEs

Table A6: Hypothesis 4: White Republicans

	Traffic Stops (1)	Mental Health (2)	No Knock (3)	Qual. Imm. (4)	Civ. Oversight (5)
Shot	−0.120	0.128	−0.142	−0.096	0.009
	(0.208)	(0.233)	(0.276)	(0.234)	(0.231)
Killed	0.125	0.284	−0.343	−0.225	−0.085
	(0.199)	(0.221)	(0.266)	(0.242)	(0.240)
Armed	0.117	0.295	0.097	0.005	0.099
	(0.212)	(0.230)	(0.243)	(0.220)	(0.239)
Estimate Diff	0.194	0.258*	0.078	0.139	0.142
	(0.142)	(0.152)	(0.158)	(0.161)	(0.141)
Houston	0.093	0.342	0.686*	0.526	0.218
	(0.383)	(0.386)	(0.397)	(0.344)	(0.391)
Jacksonville	−0.185	0.374	0.196	0.183	0.195
	(0.376)	(0.404)	(0.441)	(0.338)	(0.403)
Los Angeles	−0.606	0.330	0.129	0.626	−0.206
	(0.445)	(0.465)	(0.521)	(0.492)	(0.465)
New York City	−0.111	0.059	−0.346	0.112	0.534
	(0.337)	(0.359)	(0.373)	(0.303)	(0.361)
Philadelphia	−0.574	−0.302	−0.151	0.467	−0.440
	(0.413)	(0.467)	(0.577)	(0.536)	(0.457)
Phoenix	−0.202	0.400	−0.050	0.373	0.383
	(0.394)	(0.419)	(0.435)	(0.337)	(0.432)
San Antonio	−0.328	0.679*	0.047	0.892***	0.948**
	(0.362)	(0.405)	(0.410)	(0.346)	(0.411)
San Diego	−0.381	0.497	−0.210	0.041	0.474
	(0.422)	(0.495)	(0.458)	(0.422)	(0.461)
San Jose	0.108	0.479	−0.666	0.207	0.848
	(0.529)	(0.569)	(0.565)	(0.539)	(0.792)
Female	0.257*	0.200	0.226	0.148	0.005
	(0.154)	(0.169)	(0.202)	(0.177)	(0.187)
Age	−0.004	0.002	−0.004	−0.008	−0.006
	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)
Education	0.056	0.059	−0.067	0.075	−0.015
	(0.059)	(0.060)	(0.069)	(0.060)	(0.069)
Income	−0.022	−0.043	0.036	0.002	−0.018
	(0.026)	(0.030)	(0.031)	(0.028)	(0.030)
Children	0.191	0.234	−0.512*	0.203	0.067
	(0.203)	(0.227)	(0.266)	(0.233)	(0.223)
Registered Voter	−0.223	−0.275	0.238	−0.024	0.512
	(0.360)	(0.428)	(0.430)	(0.381)	(0.485)
Pol. Ideology	−0.295***	−0.322***	−0.258**	−0.311***	−0.250**
	(0.096)	(0.121)	(0.125)	(0.105)	(0.116)
PD Rating	−0.173**	−0.307***	−0.033	−0.113	−0.199***
	(0.068)	(0.076)	(0.088)	(0.080)	(0.077)
UoF Experience	0.002	−0.099	0.134	0.285	0.098
	(0.208)	(0.253)	(0.289)	(0.242)	(0.277)
Shot x Estimate Diff	−0.236	−0.149	0.163	0.146	−0.200
	(0.170)	(0.190)	(0.226)	(0.183)	(0.188)
Killed x Estimate Diff	−0.138	−0.049	−0.103	−0.186	−0.052
	(0.173)	(0.184)	(0.191)	(0.192)	(0.172)
Armed x Estimate Diff	−0.181	−0.230	−0.129	−0.065	0.010
	(0.184)	(0.227)	(0.240)	(0.232)	(0.226)
Constant	4.265***	4.629***	3.905***	3.906***	4.091***
	(0.691)	(0.857)	(0.789)	(0.764)	(0.877)
N	223	223	223	223	223
R^2	0.215	0.237	0.147	0.222	0.179
F Statistic (df = 25; 197)	2.152***	2.447***	1.357	2.251***	1.715**

*p < .1; **p < .05; ***p < .01
Notes: With robust SEs

A.4.5 Hypothesis 5: Rate of Unarmed Shootings

p-value of Armed x Unarmed Rate in model with traffic stops outcome and control group reference: 0.149

Table A7: Hypothesis 5 Results: Control Reference

	Traffic Stops	Mental Health	No Knock	Qual. Imm.	Civ. Oversight
	(1)	(2)	(3)	(4)	(5)
Shot	−0.104	−0.051	0.177	0.180	0.040
	(0.122)	(0.118)	(0.148)	(0.132)	(0.116)
Killed	0.175	0.013	0.305^{**}	0.097	0.144
	(0.123)	(0.119)	(0.153)	(0.133)	(0.119)
Armed	−0.116	−0.034	0.095	−0.049	0.161
	(0.122)	(0.121)	(0.148)	(0.132)	(0.114)
Unarmed Rate	−0.004	−0.003	0.007	0.006	0.010
	(0.007)	(0.007)	(0.007)	(0.007)	(0.006)
Houston	0.172	0.141	0.221	0.279^{**}	−0.007
	(0.127)	(0.120)	(0.150)	(0.137)	(0.110)
Jacksonville	0.124	0.042	0.289^{*}	−0.023	−0.059
	(0.133)	(0.133)	(0.159)	(0.153)	(0.138)
Los Angeles	−0.107	-0.187^{*}	−0.165	0.048	−0.088
	(0.103)	(0.103)	(0.124)	(0.113)	(0.102)
New York City	−0.118	-0.166^{*}	−0.135	−0.056	0.045
	(0.090)	(0.087)	(0.106)	(0.097)	(0.088)
Philadelphia	0.001	0.027	−0.014	0.012	0.189
	(0.130)	(0.126)	(0.159)	(0.141)	(0.126)
Phoenix	−0.110	0.122	−0.002	−0.040	0.014
	(0.116)	(0.112)	(0.142)	(0.128)	(0.113)
San Antonio	−0.075	0.139	−0.004	0.264^{**}	0.218^{**}
	(0.114)	(0.110)	(0.137)	(0.122)	(0.110)
San Diego	−0.018	0.086	−0.158	−0.128	−0.096
	(0.145)	(0.136)	(0.178)	(0.158)	(0.134)
San Jose					
Black	0.041	0.116^{*}	0.002	−0.056	0.132^{*}
	(0.072)	(0.066)	(0.088)	(0.079)	(0.068)
Hispanic/Latino	−0.086	0.014	-0.262^{***}	-0.241^{***}	−0.0001
	(0.064)	(0.064)	(0.079)	(0.069)	(0.064)
Other Race	−0.027	0.017	0.079	0.022	0.051
	(0.076)	(0.073)	(0.093)	(0.083)	(0.070)
Partisanship	-0.088^{***}	-0.130^{***}	-0.061^{***}	-0.066^{***}	-0.081^{***}
	(0.016)	(0.016)	(0.019)	(0.017)	(0.016)
Female	−0.040	0.128^{***}	-0.102^{*}	-0.121^{**}	−0.055
	(0.048)	(0.047)	(0.059)	(0.053)	(0.047)
Age	-0.007^{***}	−0.001	0.0003	-0.009^{***}	−0.002
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)
Education	0.057^{***}	0.066^{***}	0.082^{***}	0.032^{*}	0.020
	(0.018)	(0.017)	(0.022)	(0.019)	(0.017)
Income	0.001	−0.002	0.017^{*}	0.007	0.0003
	(0.008)	(0.007)	(0.009)	(0.008)	(0.007)
Children	0.030	−0.044	-0.192^{***}	-0.114^{*}	-0.127^{**}
	(0.060)	(0.059)	(0.073)	(0.064)	(0.059)
Registered Voter	−0.073	0.008	0.088	−0.008	0.095
	(0.078)	(0.081)	(0.095)	(0.084)	(0.079)
Pol. Ideology	-0.316^{***}	-0.283^{***}	-0.260^{***}	-0.267^{***}	-0.285^{***}
	(0.029)	(0.030)	(0.036)	(0.033)	(0.031)
Shootings Estimate	−0.00005	−0.00005	−0.00004	−0.0001	−0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
PD Rating	-0.235^{***}	-0.188^{***}	-0.088^{***}	-0.168^{***}	-0.198^{***}
	(0.021)	(0.020)	(0.025)	(0.022)	(0.020)
UoF Experience	0.032	0.032	0.195^{***}	0.120^{*}	0.103^{*}
	(0.055)	(0.054)	(0.068)	(0.062)	(0.054)
Shot x Unarmed Rate	0.003	0.003	−0.010	−0.009	0.004
	(0.008)	(0.007)	(0.009)	(0.008)	(0.007)
Killed x Unarmed Rate	−0.004	0.002	-0.024^{***}	−0.003	−0.001
	(0.007)	(0.007)	(0.009)	(0.008)	(0.007)
Armed x Unarmed Rate	0.011	0.003	−0.006	0.006	0.001
	(0.008)	(0.008)	(0.009)	(0.008)	(0.007)
Constant	5.092^{***}	5.230^{***}	3.976^{***}	4.971^{***}	4.955^{***}
	(0.178)	(0.186)	(0.221)	(0.202)	(0.189)
N	2,238	2,238	2,238	2,238	2,238
R^2	0.276	0.271	0.129	0.182	0.239
F Statistic (df = 29; 2208)	29.000^{***}	28.364^{***}	11.253^{***}	16.909^{***}	23.940^{***}

*p < .1; **p < .05; ***p < .01
Notes: With robust SEs

p-value of Armed x Unarmed Rate in model with traffic stops outcome and Shot group reference: 0.302

Table A8: Hypothesis 5 Results: Shot Reference

	Traffic Stops	Mental Health	No Knock	Qual. Imm.	Civ. Oversight
	(1)	(2)	(3)	(4)	(5)
Control	0.104	0.051	−0.177	−0.180	−0.040
	(0.122)	(0.118)	(0.148)	(0.132)	(0.116)
Killed	0.279**	0.065	0.127	−0.083	0.103
	(0.122)	(0.114)	(0.150)	(0.135)	(0.119)
Armed	−0.012	0.018	−0.083	−0.229*	0.120
	(0.121)	(0.117)	(0.145)	(0.133)	(0.114)
Unarmed Rate	−0.001	0.00004	−0.004	−0.003	0.013**
	(0.006)	(0.006)	(0.008)	(0.007)	(0.005)
Houston	0.172	0.141	0.221	0.279**	−0.007
	(0.127)	(0.120)	(0.150)	(0.137)	(0.110)
Jacksonville	0.124	0.042	0.289*	−0.023	−0.059
	(0.133)	(0.133)	(0.159)	(0.153)	(0.138)
Los Angeles	−0.107	−0.187*	−0.165	0.048	−0.088
	(0.103)	(0.103)	(0.124)	(0.113)	(0.102)
New York City	−0.118	−0.166*	−0.135	−0.056	0.045
	(0.090)	(0.087)	(0.106)	(0.097)	(0.088)
Philadelphia	0.001	0.027	−0.014	0.012	0.189
	(0.130)	(0.126)	(0.159)	(0.141)	(0.126)
Phoenix	−0.110	0.122	−0.002	−0.040	0.014
	(0.116)	(0.112)	(0.142)	(0.128)	(0.113)
San Antonio	−0.075	0.139	−0.004	0.264**	0.218**
	(0.114)	(0.110)	(0.137)	(0.122)	(0.110)
San Diego	−0.018	0.086	−0.158	−0.128	−0.096
	(0.145)	(0.136)	(0.178)	(0.158)	(0.134)
San Jose					
Black	0.041	0.116*	0.002	−0.056	0.132*
	(0.072)	(0.066)	(0.088)	(0.079)	(0.068)
Hispanic/Latino	−0.086	0.014	−0.262***	−0.241***	−0.0001
	(0.064)	(0.064)	(0.079)	(0.069)	(0.064)
Other Race	−0.027	0.017	0.079	0.022	0.051
	(0.076)	(0.073)	(0.093)	(0.083)	(0.070)
Partisanship	−0.088***	−0.130***	−0.061***	−0.066***	−0.081***
	(0.016)	(0.016)	(0.019)	(0.017)	(0.016)
Female	−0.040	0.128***	−0.102*	−0.121**	−0.055
	(0.048)	(0.047)	(0.059)	(0.053)	(0.047)
Age	−0.007***	−0.001	0.0003	−0.009***	−0.002
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)
Education	0.057***	0.066***	0.082***	0.032*	0.020
	(0.018)	(0.017)	(0.022)	(0.019)	(0.017)
Income	0.001	−0.002	0.017*	0.007	0.0003
	(0.008)	(0.007)	(0.009)	(0.008)	(0.007)
Children	0.030	−0.044	−0.192***	−0.114*	−0.127**
	(0.060)	(0.059)	(0.073)	(0.064)	(0.059)
Registered Voter	−0.073	0.008	0.088	−0.008	0.095
	(0.078)	(0.081)	(0.095)	(0.084)	(0.079)
Pol. Ideology	−0.316***	−0.283***	−0.260***	−0.267***	−0.285***
	(0.029)	(0.030)	(0.036)	(0.033)	(0.031)
Shootings Estimate	−0.00005	−0.00005	−0.00004	−0.0001	−0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
PD Rating	−0.235***	−0.188***	−0.088***	−0.168***	−0.198***
	(0.021)	(0.020)	(0.025)	(0.022)	(0.020)
UoF Experience	0.032	0.032	0.195***	0.120*	0.103*
	(0.055)	(0.054)	(0.068)	(0.062)	(0.054)
Control x Unarmed Rate	−0.003	−0.003	0.010	0.009	−0.004
	(0.008)	(0.007)	(0.009)	(0.008)	(0.007)
Killed x Unarmed Rate	−0.007	−0.0004	−0.013	0.006	−0.005
	(0.007)	(0.007)	(0.009)	(0.008)	(0.007)
Armed x Unarmed Rate	0.008	0.0002	0.005	0.015*	−0.002
	(0.008)	(0.007)	(0.009)	(0.008)	(0.007)
Constant	4.988***	5.179***	4.153***	5.150***	4.996***
	(0.180)	(0.183)	(0.218)	(0.197)	(0.188)
N	2,238	2,238	2,238	2,238	2,238
R^2	0.276	0.271	0.129	0.182	0.239
F Statistic (df = 29; 2208)	29.000***	28.364***	11.253***	16.909***	23.940***

*p < .1; **p < .05; ***p < .01
Notes: With robust SEs

A.4.6 Rate of Fatal Shootings

p-value of Killed x Fatal Rate in model with traffic stops outcome and control group reference: 0.536

Table A9: Fatal Shootings: Control Reference

	Traffic Stops	Mental Health	No Knock	Qual. Imm.	Civ. Oversight
	(1)	(2)	(3)	(4)	(5)
Shot	0.043	0.075	0.338	−0.022	0.193
	(0.224)	(0.224)	(0.266)	(0.235)	(0.216)
Killed	0.248	0.191	−0.102	0.251	0.236
	(0.220)	(0.219)	(0.276)	(0.239)	(0.223)
Armed	0.223	0.119	−0.011	−0.242	0.261
	(0.223)	(0.219)	(0.270)	(0.239)	(0.214)
Fatal Rate	0.001	0.005	−0.008	−0.002	0.007
	(0.006)	(0.006)	(0.008)	(0.007)	(0.007)
Houston	0.153	0.099	0.209^{*}	0.411^{***}	0.245^{**}
	(0.096)	(0.094)	(0.119)	(0.101)	(0.096)
Jacksonville	0.145	−0.033	0.449^{**}	0.068	−0.017
	(0.144)	(0.144)	(0.181)	(0.166)	(0.149)
Los Angeles	−0.045	−0.319	0.207	0.127	−0.242
	(0.219)	(0.213)	(0.281)	(0.243)	(0.214)
New York City	−0.071	-0.276^{*}	0.157	0.025	−0.042
	(0.172)	(0.165)	(0.221)	(0.189)	(0.167)
Philadelphia	0.030	−0.026	0.149	0.020	0.083
	(0.128)	(0.122)	(0.163)	(0.139)	(0.117)
Phoenix	−0.094	0.053	0.136	0.049	0.069
	(0.122)	(0.119)	(0.158)	(0.136)	(0.121)
San Antonio	−0.013	0.004	0.375	0.355	0.087
	(0.229)	(0.221)	(0.293)	(0.251)	(0.225)
San Diego					
San Jose	−0.044	−0.028	−0.106	0.193	0.427^{***}
	(0.180)	(0.167)	(0.207)	(0.194)	(0.159)
Black	0.038	0.115^{*}	0.0004	−0.053	0.130^{*}
	(0.072)	(0.066)	(0.088)	(0.079)	(0.068)
Hispanic/Latino	−0.088	0.015	-0.269^{***}	-0.239^{***}	−0.001
	(0.064)	(0.064)	(0.079)	(0.069)	(0.064)
Other Race	−0.024	0.018	0.079	0.021	0.052
	(0.076)	(0.073)	(0.093)	(0.083)	(0.070)
Partisanship	-0.088^{***}	-0.130^{***}	-0.062^{***}	-0.065^{***}	-0.081^{***}
	(0.016)	(0.016)	(0.019)	(0.017)	(0.016)
Female	−0.038	0.129^{***}	-0.098^{*}	-0.115^{**}	−0.054
	(0.049)	(0.047)	(0.059)	(0.053)	(0.047)
Age	-0.006^{***}	−0.001	0.0002	-0.009^{***}	−0.002
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)
Education	0.058^{***}	0.066^{***}	0.086^{***}	0.033^{*}	0.019
	(0.018)	(0.017)	(0.022)	(0.019)	(0.017)
Income	0.001	−0.002	0.017^{*}	0.007	0.0003
	(0.008)	(0.007)	(0.009)	(0.008)	(0.007)
Children	0.031	−0.043	-0.189^{***}	-0.113^{*}	-0.126^{**}
	(0.060)	(0.059)	(0.073)	(0.064)	(0.059)
Registered Voter	−0.075	0.009	0.079	−0.013	0.094
	(0.078)	(0.081)	(0.095)	(0.083)	(0.079)
Pol. Ideology	-0.315^{***}	-0.283^{***}	-0.259^{***}	-0.267^{***}	-0.285^{***}
	(0.029)	(0.030)	(0.036)	(0.033)	(0.031)
Shootings Estimate	−0.0001	−0.00005	−0.00004	−0.0001	−0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
PD Rating	-0.234^{***}	-0.188^{***}	-0.089^{***}	-0.170^{***}	-0.198^{***}
	(0.021)	(0.020)	(0.025)	(0.022)	(0.020)
UoF Experience	0.038	0.034	0.194^{***}	0.125^{**}	0.105^{*}
	(0.055)	(0.054)	(0.069)	(0.062)	(0.054)
Shot x Fatal Rate	−0.002	−0.002	−0.007	0.002	−0.002
	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)
Killed x Fatal Rate	−0.003	−0.003	0.002	−0.004	−0.002
	(0.005)	(0.005)	(0.006)	(0.005)	(0.005)
Armed x Fatal Rate	−0.004	−0.002	0.001	0.006	−0.002
	(0.005)	(0.004)	(0.006)	(0.005)	(0.004)
Constant	4.967^{***}	5.057^{***}	4.235^{***}	5.040^{***}	4.752^{***}
	(0.264)	(0.272)	(0.319)	(0.291)	(0.280)
N	2,238	2,238	2,238	2,238	2,238
R^2	0.275	0.272	0.127	0.182	0.239
F Statistic (df = 29; 2208)	28.847^{***}	28.380^{***}	11.071^{***}	16.936^{***}	23.935^{***}

*p < .1; **p < .05; ***p < .01
Notes: With robust SEs

p-value of Killed x Fatal Rate in model with traffic stops outcome and Shot group reference: 0.913

Table A10: Fatal Shootings: Shot Reference

	Traffic Stops (1)	Mental Health (2)	No Knock (3)	Qual. Imm. (4)	Civ. Oversight (5)
Control	−0.043	−0.075	−0.338	0.022	−0.193
	(0.224)	(0.224)	(0.266)	(0.235)	(0.216)
Killed	0.206	0.117	−0.441	0.272	0.043
	(0.224)	(0.217)	(0.275)	(0.240)	(0.219)
Armed	0.180	0.045	−0.349	−0.220	0.068
	(0.225)	(0.216)	(0.268)	(0.238)	(0.210)
Fatal Rate	−0.001	0.003	−0.014*	−0.0001	0.005
	(0.007)	(0.006)	(0.008)	(0.007)	(0.006)
Houston	0.153	0.099	0.209*	0.411***	0.245**
	(0.096)	(0.094)	(0.119)	(0.101)	(0.096)
Jacksonville	0.145	−0.033	0.449**	0.068	−0.017
	(0.144)	(0.144)	(0.181)	(0.166)	(0.149)
Los Angeles	−0.045	−0.319	0.207	0.127	−0.242
	(0.219)	(0.213)	(0.281)	(0.243)	(0.214)
New York City	−0.071	−0.276*	0.157	0.025	−0.042
	(0.172)	(0.165)	(0.221)	(0.189)	(0.167)
Philadelphia	0.030	−0.026	0.149	0.020	0.083
	(0.128)	(0.122)	(0.163)	(0.139)	(0.117)
Phoenix	−0.094	0.053	0.136	0.049	0.069
	(0.122)	(0.119)	(0.158)	(0.136)	(0.121)
San Antonio	−0.013	0.004	0.375	0.355	0.087
	(0.229)	(0.221)	(0.293)	(0.251)	(0.225)
San Diego					
San Jose	−0.044	−0.028	−0.106	0.193	0.427***
	(0.180)	(0.167)	(0.207)	(0.194)	(0.159)
Black	0.038	0.115*	0.0004	−0.053	0.130*
	(0.072)	(0.066)	(0.088)	(0.079)	(0.068)
Hispanic/Latino	−0.088	0.015	−0.269***	−0.239***	−0.001
	(0.064)	(0.064)	(0.079)	(0.069)	(0.064)
Other Race	−0.024	0.018	0.079	0.021	0.052
	(0.076)	(0.073)	(0.093)	(0.083)	(0.070)
Partisanship	−0.088***	−0.130***	−0.062***	−0.065***	−0.081***
	(0.016)	(0.016)	(0.019)	(0.017)	(0.016)
Female	−0.038	0.129***	−0.098*	−0.115**	−0.054
	(0.049)	(0.047)	(0.059)	(0.053)	(0.047)
Age	−0.006***	−0.001	0.0002	−0.009***	−0.002
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)
Education	0.058***	0.066***	0.086***	0.033*	0.019
	(0.018)	(0.017)	(0.022)	(0.019)	(0.017)
Income	0.001	−0.002	0.017*	0.007	0.0003
	(0.008)	(0.007)	(0.009)	(0.008)	(0.007)
Children	0.031	−0.043	−0.189***	−0.113*	−0.126**
	(0.060)	(0.059)	(0.073)	(0.064)	(0.059)
Registered Voter	−0.075	0.009	0.079	−0.013	0.094
	(0.078)	(0.081)	(0.095)	(0.083)	(0.079)
Pol. Ideology	−0.315***	−0.283***	−0.259***	−0.267***	−0.285***
	(0.029)	(0.030)	(0.036)	(0.033)	(0.031)
Shootings Estimate	−0.0001	−0.00005	−0.00004	−0.0001	−0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
PD Rating	−0.234***	−0.188***	−0.089***	−0.170***	−0.198***
	(0.021)	(0.020)	(0.025)	(0.022)	(0.020)
UoF Experience	0.038	0.034	0.194***	0.125**	0.105*
	(0.055)	(0.054)	(0.069)	(0.062)	(0.054)
Control x Fatal Rate	0.002	0.002	0.007	−0.002	0.002
	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)
Killed x Fatal Rate	−0.0005	−0.001	0.008	−0.006	−0.0001
	(0.005)	(0.004)	(0.006)	(0.005)	(0.004)
Armed x Fatal Rate	−0.002	−0.001	0.007	0.004	0.0005
	(0.005)	(0.004)	(0.005)	(0.005)	(0.004)
Constant	5.010***	5.132***	4.573***	5.018***	4.945***
	(0.271)	(0.271)	(0.322)	(0.292)	(0.275)
N	2,238	2,238	2,238	2,238	2,238
R^2	0.275	0.272	0.127	0.182	0.239
F Statistic (df = 29; 2208)	28.847***	28.380***	11.071***	16.936***	23.935***

*p < .1; **p < .05; ***p < .01
Notes: With robust SEs

A.5 Exploratory Results

Table A11: Main Effects for High Over-Estimators (Shootings Estimate >= 75)

	Traffic Stops (1)	Mental Health (2)	No Knock (3)	Qual. Imm. (4)	Civ. Oversight (5)
Shot	0.155	0.044	0.057	0.075	0.091
	(0.159)	(0.149)	(0.204)	(0.174)	(0.151)
Killed	0.232	0.122	−0.149	0.053	0.196
	(0.165)	(0.161)	(0.218)	(0.177)	(0.161)
Armed	0.111	0.133	0.007	0.065	0.228
	(0.160)	(0.156)	(0.205)	(0.168)	(0.150)
N	460	460	460	460	460
R^2	0.249	0.229	0.122	0.165	0.219
F Statistic (df = 26; 433)	5.521***	4.955***	2.316***	3.288***	4.664***

*p < .1; **p < .05; ***p < .01
Notes: With robust SEs, including covariates

Table A12: Main Effects for Under-Estimators (Shootings Estimate <= 5)

	Traffic Stops (1)	Mental Health (2)	No Knock (3)	Qual. Imm. (4)	Civ. Oversight (5)
Shot	−0.087	−0.056	−0.190	0.042	0.008
	(0.156)	(0.159)	(0.172)	(0.161)	(0.149)
Killed	0.087	−0.095	−0.029	0.131	−0.062
	(0.161)	(0.164)	(0.187)	(0.171)	(0.158)
Armed	−0.044	−0.085	0.039	−0.051	0.206
	(0.153)	(0.165)	(0.176)	(0.168)	(0.146)
N	473	473	473	473	473
R^2	0.218	0.258	0.127	0.150	0.263
F Statistic (df = 26; 446)	4.793***	5.974***	2.496***	3.021***	6.118***

*p < .1; **p < .05; ***p < .01
Notes: With robust SEs, including covariates

Table A13: Main Effects for Attentive Respondents (Answered Attention Check Correctly)

	Traffic Stops	Mental Health	No Knock	Qual. Imm.	Civ. Oversight
	(1)	(2)	(3)	(4)	(5)
Shot	−0.032	−0.042	−0.002	0.058	0.086
	(0.089)	(0.083)	(0.108)	(0.098)	(0.082)
Killed	0.084	0.001	0.076	0.037	0.019
	(0.087)	(0.081)	(0.109)	(0.097)	(0.085)
Armed	0.042	0.058	0.020	0.064	0.223***
	(0.086)	(0.078)	(0.107)	(0.097)	(0.078)
N	1,311	1,311	1,311	1,311	1,311
R^2	0.317	0.295	0.147	0.200	0.271
F Statistic (df = 26; 1284)	22.892***	20.706***	8.543***	12.358***	18.364***

*p < .1; **p < .05; ***p < .01
Notes: With robust SEs, including covariates

Table A14: Interactive Effects of Treatments with Attentiveness

	Traffic Stops	Mental Health	No Knock	Qual. Imm.	Civ. Oversight
	(1)	(2)	(3)	(4)	(5)
Shot	−0.139	0.008	0.091	0.061	0.078
	(0.106)	(0.106)	(0.127)	(0.111)	(0.105)
Killed	0.152	0.090	−0.176	0.085	0.265***
	(0.105)	(0.106)	(0.131)	(0.112)	(0.103)
Armed	−0.019	−0.098	0.020	−0.017	0.083
	(0.105)	(0.110)	(0.129)	(0.112)	(0.105)
Attentive	0.057	0.142	0.054	0.080	0.186**
	(0.099)	(0.097)	(0.120)	(0.105)	(0.094)
Shot x Attentive	0.125	−0.044	−0.101	−0.012	0.015
	(0.138)	(0.135)	(0.167)	(0.148)	(0.133)
Killed x Attentive	−0.061	−0.078	0.261	−0.051	−0.239*
	(0.136)	(0.134)	(0.171)	(0.148)	(0.133)
Armed x Attentive	0.069	0.160	−0.010	0.067	0.145
	(0.136)	(0.135)	(0.167)	(0.148)	(0.131)
N	2,238	2,238	2,238	2,238	2,238
R^2	0.276	0.276	0.129	0.182	0.246
F Statistic (df = 30; 2207)	28.085***	28.045***	10.885***	16.318***	24.052***

*p < .1; **p < .05; ***p < .01
Notes: With robust SEs, including covariates

Table A15: Main Effects for Independents

	Traffic Stops	Mental Health	No Knock	Qual. Imm.	Civ. Oversight
	(1)	(2)	(3)	(4)	(5)
Shot	-0.334^{*}	-0.148	0.143	0.128	0.181
	(0.186)	(0.178)	(0.201)	(0.184)	(0.161)
Killed	0.161	-0.063	0.290	0.118	0.123
	(0.182)	(0.178)	(0.207)	(0.187)	(0.181)
Armed	-0.052	-0.064	-0.076	0.036	0.395^{**}
	(0.183)	(0.172)	(0.208)	(0.191)	(0.161)
N	381	381	381	381	381
R^2	0.248	0.196	0.136	0.170	0.191
F Statistic (df = 25; 355)	4.683^{***}	3.463^{***}	2.228^{***}	2.902^{***}	3.359^{***}

$^{*}p < .1$; $^{**}p < .05$; $^{***}p < .01$
Notes: With robust SEs, including covariates

Table A16: Demographics Associated with Reform Support

	Traffic Stops	Mental Health	No Knock	Qual. Imm.	Civ. Oversight
	(1)	(2)	(3)	(4)	(5)
Black	0.038	0.115*	0.001	−0.052	0.129*
	(0.072)	(0.066)	(0.087)	(0.079)	(0.068)
Hispanic/Latino	−0.086	0.015	−0.269***	−0.240***	0.002
	(0.064)	(0.064)	(0.079)	(0.069)	(0.064)
Other Race	−0.029	0.016	0.084	0.023	0.060
	(0.076)	(0.073)	(0.093)	(0.083)	(0.070)
Partisanship	−0.088***	−0.130***	−0.062***	−0.066***	−0.082***
	(0.016)	(0.016)	(0.019)	(0.017)	(0.016)
Female	−0.038	0.128***	−0.097*	−0.116**	−0.055
	(0.048)	(0.047)	(0.059)	(0.053)	(0.047)
Age	−0.006***	−0.001	0.0004	−0.009***	−0.002
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)
Education	0.058***	0.066***	0.085***	0.034*	0.020
	(0.018)	(0.017)	(0.022)	(0.019)	(0.017)
Income	0.002	−0.001	0.017*	0.007	0.001
	(0.008)	(0.007)	(0.009)	(0.008)	(0.007)
Children	0.025	−0.046	−0.187**	−0.112*	−0.125**
	(0.060)	(0.059)	(0.073)	(0.064)	(0.059)
Registered Voter	−0.077	0.007	0.076	−0.016	0.082
	(0.078)	(0.081)	(0.095)	(0.083)	(0.079)
Pol. Ideology	−0.312***	−0.282***	−0.259***	−0.266***	−0.284***
	(0.029)	(0.030)	(0.036)	(0.033)	(0.031)
Shootings Estimate	−0.0001	−0.00005	−0.00004	−0.0001	−0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
PD Rating	−0.238***	−0.188***	−0.087***	−0.169***	−0.197***
	(0.021)	(0.020)	(0.025)	(0.022)	(0.020)
UoF Experience	0.035	0.032	0.199***	0.121*	0.103*
	(0.055)	(0.054)	(0.068)	(0.062)	(0.054)
Houston	0.143	0.123	0.135	0.415***	0.286**
	(0.112)	(0.110)	(0.135)	(0.118)	(0.113)
Jacksonville	0.109	0.031	0.248	0.057	0.111
	(0.139)	(0.140)	(0.166)	(0.159)	(0.149)
Los Angeles	−0.109	−0.191*	−0.188	0.095	0.008
	(0.115)	(0.114)	(0.137)	(0.125)	(0.116)
New York City	−0.124	−0.172*	−0.166	0.0001	0.161
	(0.103)	(0.100)	(0.122)	(0.111)	(0.105)
Philadelphia	−0.0002	0.027	−0.018	0.009	0.189
	(0.131)	(0.126)	(0.160)	(0.141)	(0.126)
Phoenix	−0.122	0.113	−0.048	0.041	0.182
	(0.123)	(0.121)	(0.151)	(0.135)	(0.126)
San Antonio	−0.080	0.133	−0.032	0.326**	0.347***
	(0.124)	(0.121)	(0.149)	(0.132)	(0.124)
San Diego	−0.033	0.073	−0.224	−0.013	0.145
	(0.144)	(0.139)	(0.179)	(0.156)	(0.144)
San Jose	−0.047	−0.029	−0.111	0.198	0.415***
	(0.180)	(0.167)	(0.207)	(0.193)	(0.157)
Constant	5.064***	5.210***	4.105***	5.016***	5.042***
	(0.165)	(0.168)	(0.200)	(0.184)	(0.174)
N	2,238	2,238	2,238	2,238	2,238
R^2	0.272	0.271	0.126	0.180	0.236
F Statistic (df = 23; 2214)	35.955***	35.791***	13.840***	21.153***	29.763***

*p < .1; **p < .05; ***p < .01
Notes: With robust SEs

Table A17: Interaction Models of Race and Partisanship

	Traffic Stops	Mental Health	No Knock	Qual. Imm.	Civ. Oversight
	(1)	(2)	(3)	(4)	(5)
Non-Black	0.114	−0.071	0.043	0.209	0.121
	(0.118)	(0.106)	(0.142)	(0.129)	(0.108)
Partisanship	−0.033	-0.129^{***}	−0.019	0.013	−0.006
	(0.040)	(0.040)	(0.047)	(0.045)	(0.039)
Female	0.016	0.172^{***}	−0.086	−0.084	−0.008
	(0.050)	(0.048)	(0.059)	(0.054)	(0.048)
Age	-0.007^{***}	-0.003^{*}	0.0002	-0.009^{***}	-0.003^{*}
	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)
Education	0.056^{***}	0.065^{***}	0.090^{***}	0.035^{*}	0.018
	(0.018)	(0.018)	(0.022)	(0.019)	(0.017)
Income	0.002	−0.002	0.020^{**}	0.010	0.001
	(0.008)	(0.008)	(0.009)	(0.008)	(0.007)
Children	−0.084	-0.126^{**}	-0.250^{***}	-0.206^{***}	-0.214^{***}
	(0.061)	(0.060)	(0.072)	(0.064)	(0.060)
Registered Voter	−0.085	−0.002	0.059	−0.029	0.076
	(0.080)	(0.081)	(0.095)	(0.083)	(0.080)
Pol. Ideology	-0.367^{***}	-0.326^{***}	-0.284^{***}	-0.308^{***}	-0.325^{***}
	(0.029)	(0.029)	(0.035)	(0.032)	(0.030)
Shootings Estimate	−0.00003	−0.00002	−0.00003	−0.00003	−0.00004
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
UoF Experience	0.142^{**}	0.119^{**}	0.226^{***}	0.188^{***}	0.195^{***}
	(0.057)	(0.054)	(0.068)	(0.062)	(0.054)
Houston	0.198^{*}	0.173	0.139	0.443^{***}	0.348^{***}
	(0.115)	(0.111)	(0.137)	(0.121)	(0.115)
Jacksonville	0.204	0.088	0.322^{*}	0.158	0.192
	(0.144)	(0.145)	(0.169)	(0.164)	(0.154)
Los Angeles	0.036	−0.076	−0.124	0.206	0.142
	(0.118)	(0.116)	(0.138)	(0.128)	(0.119)
New York City	−0.013	−0.083	−0.116	0.085	0.267^{**}
	(0.105)	(0.101)	(0.123)	(0.113)	(0.107)
Philadelphia	0.127	0.111	0.065	0.130	0.293^{**}
	(0.137)	(0.127)	(0.162)	(0.145)	(0.129)
Phoenix	−0.004	0.199	0.005	0.135	0.281^{**}
	(0.127)	(0.124)	(0.153)	(0.138)	(0.130)
San Antonio	−0.092	0.136	−0.096	0.278^{**}	0.359^{***}
	(0.129)	(0.122)	(0.150)	(0.135)	(0.126)
San Diego	−0.038	0.068	−0.210	−0.006	0.149
	(0.151)	(0.142)	(0.179)	(0.158)	(0.148)
San Jose	0.013	0.022	−0.049	0.265	0.480^{***}
	(0.183)	(0.173)	(0.211)	(0.199)	(0.164)
Non-Black x Partisanship	-0.088^{**}	−0.023	−0.053	-0.105^{**}	-0.111^{***}
	(0.042)	(0.042)	(0.049)	(0.047)	(0.041)
Constant	4.430^{***}	4.913^{***}	3.803^{***}	4.378^{***}	4.539^{***}
	(0.199)	(0.195)	(0.234)	(0.209)	(0.199)
N	2,238	2,238	2,238	2,238	2,238
R^2	0.224	0.239	0.115	0.154	0.202
F Statistic (df = 21; 2216)	30.529^{***}	33.060^{***}	13.667^{***}	19.266^{***}	26.630^{***}

$^{*}p < .1$; $^{**}p < .05$; $^{***}p < .01$
Notes: With robust SEs

A.6 Additional Information on the Shootings Estimates

Table A18 describes respondents' shootings estimates and the factual statistics. Estimates vary substantially but are generally proximate to the factual numbers reported by police departments.

Table A18: Shootings Statistics and Survey Respondent Estimates by City

		Police Shootings					
		Factual	*Estimates*				
City	Sample	Total	Min	Median	Mean	Max	Avg. Estimate Diff in Logs
Dallas	171	5	1	14	35	500	1.03
Houston	342	18	0	20	61	2500	0.11
Jacksonville	127	19	0	12	39	911	-0.31
Los Angeles	325	22	0	25	200	8777	0.44
New York City	822	9	0	20	144	7500	1.09
Philadelphia	172	13	0	20	77	1000	0.63
Phoenix	191	25	0	20	66	3000	-0.10
San Antonio	221	17	0	12	37	900	-0.14
San Diego	131	9	0	10	42	1000	0.27
San Jose	73	5	0	10	19	150	0.61
Overall	2575		0	20	99	8777	0.53

Note: Avg. Estimate Diff is a city-level measure of how far off estimates are, on average, compared to the factual total. For each city, we average the respondent-level differences between the log of the estimate + 1 and the log of the factual total + 1.

Table A19 presents the bivariate association between shootings estimates and reform support. Table A20 presents the bivariate association between our estimate difference measure and reform support. Estimate Diff measures how far off respondents' police shootings estimates are compared to the actual number of shootings in their cities. For each respondent, we subtract the log of the actual number of shootings in his/her city + 1 from the log of his/her estimate + 1.

Table A21 reports associations between demographic factors and shootings estimates, and Table A22 reports associations between demographic factors and the estimate difference measure.

Table A19: Association between Shootings Estimate and Reform Support

	Traffic Stops	Mental Health	No Knock	Qual. Imm.	Civ. Oversight
	(1)	(2)	(3)	(4)	(5)
Shootings Estimate	0.0001	0.00004	−0.00000	0.0001	0.00003
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.00005)
Controls	No	No	No	No	No
N	2,568	2,568	2,568	2,568	2,568
R^2	0.001	0.0002	0.00000	0.0004	0.0001
F Statistic (df = 1; 2566)	1.646	0.406	0.002	0.902	0.262

$^{*}p < .1$; $^{**}p < .05$; $^{***}p < .01$
Notes: With robust SEs

Table A20: Association between Estimate Diff and Reform Support

	Traffic Stops	Mental Health	No Knock	Qual. Imm.	Civ. Oversight
	(1)	(2)	(3)	(4)	(5)
Estimate Diff	0.124***	0.127***	0.082***	0.107***	0.102***
	(0.016)	(0.017)	(0.019)	(0.017)	(0.016)
Controls	No	No	No	No	No
N	2,568	2,568	2,568	2,568	2,568
R^2	0.021	0.023	0.007	0.015	0.016
F Statistic (df = 1; 2566)	55.838***	61.297***	19.083***	38.337***	41.609***

$^{*}p < .1$; $^{**}p < .05$; $^{***}p < .01$
Notes: With robust SEs

Table A21: Demographics Associated with Shootings Estimates

	Shootings Estimate
Black	42.905
	(29.084)
Hispanic/Latino	11.581
	(18.903)
Other Race	46.917
	(39.301)
Partisanship	−1.855
	(5.103)
Female	−1.709
	(20.581)
Age	-1.637^{***}
	(0.608)
Education	−1.611
	(9.921)
Income	0.045
	(4.572)
Children	−9.054
	(23.958)
Registered Voter	−7.443
	(33.846)
Pol. Ideology	0.021
	(9.267)
PD Rating	-15.480^{**}
	(7.414)
UoF Experience	21.167
	(20.432)
Houston	16.798
	(13.377)
Jacksonville	12.430
	(14.189)
Los Angeles	163.320^{***}
	(47.903)
New York City	88.124^{***}
	(21.455)
Philadelphia	36.844^{**}
	(16.649)
Phoenix	37.263^{*}
	(21.242)
San Antonio	14.123
	(12.354)
San Diego	11.689
	(12.784)
San Jose	−14.682
	(17.815)
Constant	162.720^{***}
	(46.359)
N	2,238
R^2	0.031
F Statistic	3.187^{***} (df = 22; 2215)

$^{*}p < .1$; $^{**}p < .05$; $^{***}p < .01$
Notes: With robust SEs

Table A22: Demographics Associated with Estimate Diff

	Estimate Diff
Black	0.187^{**}
	(0.090)
Hispanic/Latino	0.102
	(0.079)
Other Race	0.172^{*}
	(0.104)
Partisanship	-0.059^{***}
	(0.020)
Female	0.011
	(0.063)
Age	-0.012^{***}
	(0.002)
Education	0.042^{*}
	(0.024)
Income	0.021^{**}
	(0.010)
Children	-0.158^{**}
	(0.077)
Registered Voter	0.023
	(0.117)
Pol. Ideology	-0.013
	(0.037)
PD Rating	-0.221^{***}
	(0.025)
UoF Experience	0.151^{**}
	(0.072)
Constant	1.534^{***}
	(0.189)
N	2,238
R^2	0.099
F Statistic	18.843^{***} (df = 13; 2224)

$^{*}p < .1$; $^{**}p < .05$; $^{***}p < .01$
Notes: With robust SEs

A.7 Assessing Respondent Attentiveness

Unfortunately, we did not include a manipulation check in our survey. We aimed to assess respondent attentiveness, then, in two ways. First, we explored potential heterogeneity by survey length.

We filter our respondents that completed the survey between the first and third quartile of completion (in minutes). These are all respondents who spent between 5.8 and 13.3 minutes. While this is not a manipulation check per se, it does limit our sample to those who spent a near average amount of time completing the survey, as opposed to those respondents who spent under two minutes or over 100 minutes. We hope that these respondents are paying attention and reading the treatments. Table A23 shows this subset. We find similarly null effects for these assumed "attentive" respondents. These results reassure us that the null effects are not limited to those inattentive respondents.

Table A23: Hypothesis 1 Results Subsetting to Between First and Third Quartile Respondents

	Traffic Stops	Mental Health	No Knock	Qual. Imm.	Civ. Oversight
	(1)	(2)	(3)	(4)	(5)
Shot	−0.120	−0.061	−0.054	0.003	0.027
	(0.098)	(0.095)	(0.119)	(0.106)	(0.095)
Killed	0.119	0.080	0.033	0.045	0.124
	(0.093)	(0.091)	(0.119)	(0.103)	(0.091)
Armed	0.009	−0.019	0.081	0.049	0.160*
	(0.091)	(0.091)	(0.113)	(0.102)	(0.085)
Houston	0.134	0.387**	0.321*	0.439***	0.523***
	(0.163)	(0.163)	(0.192)	(0.161)	(0.157)
Jacksonville	0.139	0.128	0.401*	−0.214	0.091
	(0.186)	(0.193)	(0.224)	(0.214)	(0.214)
Los Angeles	−0.080	−0.098	0.050	0.040	0.182
	(0.166)	(0.171)	(0.192)	(0.174)	(0.162)
New York City	−0.163	0.043	−0.068	−0.036	0.390***
	(0.149)	(0.149)	(0.172)	(0.152)	(0.146)
Philadelphia	−0.023	0.196	0.104	−0.078	0.410**
	(0.189)	(0.184)	(0.225)	(0.189)	(0.172)
Phoenix	−0.208	0.203	−0.141	−0.003	0.396**
	(0.171)	(0.178)	(0.206)	(0.181)	(0.172)
San Antonio	−0.209	0.327*	0.256	0.301*	0.585***
	(0.176)	(0.177)	(0.206)	(0.179)	(0.175)
San Diego	−0.094	0.219	0.069	0.012	0.384**
	(0.198)	(0.206)	(0.242)	(0.221)	(0.193)
San Jose	−0.102	0.159	−0.271	0.122	0.544**
	(0.315)	(0.240)	(0.314)	(0.274)	(0.232)
Black	−0.062	0.028	−0.079	−0.123	0.056
	(0.097)	(0.094)	(0.126)	(0.113)	(0.099)
Hispanic/Latino	−0.143	−0.057	−0.297***	−0.246**	0.097
	(0.092)	(0.093)	(0.113)	(0.101)	(0.090)
Other Race	−0.051	−0.041	0.112	−0.052	0.145
	(0.114)	(0.112)	(0.136)	(0.125)	(0.100)
Partisanship	−0.100***	−0.143***	−0.063**	−0.073***	−0.074***
	(0.023)	(0.024)	(0.028)	(0.025)	(0.023)
Female	−0.073	0.154**	−0.130	−0.082	−0.077
	(0.068)	(0.067)	(0.082)	(0.075)	(0.066)
Age	−0.003	−0.0004	0.004	−0.004	−0.0005
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)
Education	0.085***	0.085***	0.078**	0.035	0.014
	(0.026)	(0.025)	(0.031)	(0.027)	(0.024)
Income	−0.007	0.005	0.024*	0.0003	−0.001
	(0.011)	(0.011)	(0.013)	(0.012)	(0.011)
Children	0.137	0.034	−0.275**	−0.055	−0.158*
	(0.090)	(0.084)	(0.108)	(0.095)	(0.085)
Registered Voter	−0.202*	−0.111	−0.094	−0.143	−0.011
	(0.107)	(0.112)	(0.131)	(0.114)	(0.105)
Pol. Ideology	−0.308***	−0.229***	−0.257***	−0.296***	−0.250***
	(0.042)	(0.043)	(0.054)	(0.047)	(0.045)
Shootings Estimate	−0.00004	−0.00002	0.00002	0.0001	−0.00001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
PD Rating	−0.243***	−0.188***	−0.072*	−0.185***	−0.250***
	(0.030)	(0.030)	(0.037)	(0.032)	(0.030)
UoF Experience	0.056	0.048	0.169*	0.109	0.069
	(0.078)	(0.079)	(0.099)	(0.090)	(0.076)
Constant	5.057***	4.904***	3.987***	5.053***	4.904***
	(0.246)	(0.267)	(0.296)	(0.267)	(0.254)
N	1,129	1,129	1,129	1,129	1,129
R^2	0.284	0.254	0.132	0.192	0.253
F Statistic (df = 26; 1102)	16.814***	14.424***	6.430***	10.052***	14.335***

*p < .1; **p < .05; ***p < .01
Notes: With robust SEs

Second, we looked into the survey length (in minutes) between the control condition and all of our treatment conditions pooled together. We ran a t-test comparing the length of time the control respondents spent on the survey to the length of time all the treatment respondents spent on the survey. This comparison was insignificant ($t = 0.66354, p = 0.5072$). However, as above, we were concerned about inattentive respondents; those that spent far too long on the survey, for example. When we subset to *only those respondents* that took less than 100 minutes (which is 95% of the data), we do see a marginally statistically significant difference in survey length between the control and treatment conditions ($t = -1.921, p = 0.05496$). The control group spent an average of 10.6 minutes on the survey, while the treatment groups spent an average of 11.5 minutes. While not conclusive, these comparisons suggest that at least for those respondents who we think are attentive, the treatment groups spent more time on the survey than the control group.

A.8 References

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